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Price Dynamics and Speculators in Crude Oil Futures Market

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Abstract

This paper examines the behaviour of crude oil futures price and volatility, analyzes the relationship between speculative traders' positions and returns, and investigates whether speculative traders' position changes have a significant effect on crude oil price. It also studies how speculation factor influence crude oil returns and volatility, whether returns are related to risks, and whether financial crises increase volatility in crude oil futures markets. The empirical results from Granger causality reveal that return lead speculative position, which indicates that non-commercial or managed money traders are a class of positive feedback traders or trend followers; and also reveal that the position changes held by speculative traders will cause crude oil price movement. Based on the estimation results of GARCH(1,1) model we verify position changes of non-commercial or managed money traders can impact crude oil futures returns significantly, and indicate returns are not related to conditional variance. Moreover, during the financial crisis, crude oil futures return shows an extreme large volatility. These findings can help us better understand price discovery process in crude oil futures market, and is useful in risk management and financial engineering.

Keyword: crude oil futures; price dynamics; speculation; noncommercial positions; managed money positions; decision engineering

1. Introduction

In recent years, the importance of commodities, especially oil, as common investment alternatives to traditional markets has increased in recent years. This leads to more speculation in crude oil markets than before, and may make the mechanism of price determination a little different. We often notice articles in newspapers that discuss the effects of speculation activities, but few conduct quantitative analyses, or model the effects. For example, many comments in newspapers imply that speculative activities of funds in the energy market have recently pushed up the price of oil, making it deviate from levels determined by fundamentals, and have increased volatility. Extant literature has discussed the relationship between traders' positions and market prices, but these studies mainly focus on forecasting ability of traders and use Granger causality tests for analysis (Hartzmark, 1991; Leuthold et al., 1994; Buchanan et al., 2001; Wang, 2001, 2002; Sanders et al., 2004) [1-6]. Although researchers have examined the level and adequacy of speculation, flows of funds, and forecasting ability of traders, in futures markets, few have measured the magnitude of effects of traders' especially funds' trading activities, on crude oil futures markets and price volatility. This paper tries to investigate this very interesting question: what's the relationship of trading activities and price movements, and what are the effects of speculation on price volatility. In this paper, we discuss speculative traders' positions more thoroughly, and incorporate this factor into a model to measure the extent of its impact on crude oil futures returns and volatility. This study can reveal the speculative activities of funds in some degree.

Different theories explain different mechanisms of price determination. According to the classical economic theory, market fundamentals, especially supply and demand, should be the major factors that determine the price and drive its volatility. The efficient market hypothesis (EMH) says if financial markets are information efficient, then the price of traded assets reflects all known information and, therefore, is unbiased, in the sense that it reflects the collective beliefs of all investors about future prospects. The behavioural finance theory asserts that asset prices can change without changes in fundamentals. For example, volatility can be induced by anomalies and mass psychology (Deaton and Laroque, 1992, 1996[7, 8]; Chambers, 1996[9]; Shiller,

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2003[10]; etc). Our study can provide a supplement to these theories and make us understand price discovery process more thoroughly.

To measure the effect of trading activities on price volatility in futures markets is difficult since it is very difficult to track the activities of different traders. Fortunately, the Commodity Futures Trading Commission (CFTC) collects data on composition of open interest for all futures contracts, and releases the Commitments of Traders (COT) report to the public. We can analyze this report to get some information about activities of different traders. In the COT report, open interest is divided into reporting and non-reporting traders, wherein traders holding positions in excess of CFTC prescribed levels report their positions. Reporting traders are further categorized as commercials or non-commercials. Commercials are those associated with an underlying cash-related business, and are commonly considered to be hedgers. Non-commercials are not involved in an underlying cash business; they are referred to as speculators. Furthermore, the reported level of non-commercial activity is generally considered to be speculative activities of managed futures or commodity funds.

We notice that there are some limitations in the COT data. For example, we know nothing about the motives of non-reporting traders; these traders may be hedgers, speculators, or market makers. Furthermore, as Sanders et al. (2004)[6] has pointed out that the disaggregating of reporting traders into commercial and non-commercial market participants has potential sources of error. In particular, commercial traders may not always be hedgers, and hedgers may not always be hedging. True hedging positions are some subsets of commercial traders' positions. Total commercial positions are likely to reflect very diverse motives. This conclusion is consistent with findings of Ederington and Lee (2002)[11], who examined commercial traders in the heating oil market. To get over this problem in COT reports, some studies use non-public data to break down market participants into more groups, however these positions data is not available to the public. To obtain a true picture of speculators positions is very difficult. On the other hand, there are no obvious incentives for a trader to classify itself as a speculator, and it would seem particularly difficult for a CTA to describe itself as a commercial trader. Thus, reported non-commercial positions in the COT report most likely represent a relatively pure subset of total speculative positions, especially those held by managed funds. Therefore, we can still use non-commercial positions in the COT reports to get some information about speculation by managed funds indirectly.

To increases transparency, the CFTC began publishing a Disaggregated Commitments of Traders (DCOT) report on September 4, 2009, historical data for which are available back to June 13, 2006. The DCOT report separates reportable traders into four categories of traders: producer/merchant/processor/user, swap dealers, managed money, and other reportables. The CFTC removes swap dealers from commercial category and creates new "swap dealers" classification for reporting purposes. "Managed money" for the purpose of this report, is a registered commodity trading advisor (CTA), a registered commodity pool operator (CPO), or an unregistered fund identified by CFTC. These traders are engaged in managing and conducting organized futures trading on behalf of clients. Every other reportable trader that is not placed into one of the other three categories is placed into the "other reportables" category. The DCOT sets out open interest by long, short, and spreading for the three categories of traders—"swap dealers," "managed money," and "other reportables." For the "producer/merchant/processor/user" category, open interest is reported only by long or short positions. This paper makes use of both COT report and DCOT report to analyze the speculation activities.

2. Data and statistics

We use WTI (NYMEX) futures prices, rather than spot prices, as the study sample. Daily closing prices of the nearest contract of WTI futures (RCLC1 Cushing, Oklahoma, Crude Oil Future Contract 1) are from EIA. This price series is used as the crude oil futures price. Based on this price series, returns are calculated as the change of the logarithm of the daily closing price of crude oil futures, i.e. $R_t = \ln(P_t / P_{t-1})$. The descriptive statistics of price and returns are shown in Table 1. Also we report the autocorrelation and partial correlation of return and squared return in Table 1. The return series is a stationary series based on the augmented Dickey-Fuller (ADF) unit root test.

This paper makes use of both COT report and DCOT report to analyze the speculation activities. We use non-commercial positions in the COT report and managed money positions in the DCOT report to construct indicators to reflect speculative trading activities. The net long positions (*NL*) is defines as the long minus short position. And also we use the percent net long to capture the net long positions of speculative traders. The percent net long (*PNL*) position is calculated as long positions minus short positions, divided by the sum of all positions; the *PNL* for non-commercial positions, i.e. *NPNL* is:

$$NPNL_t = \frac{NCL_t - NCS_t}{NCL_t + NCS_t + 2\left(NCSP_t\right)} \tag{1}$$

where *NCL*, *NCS*, and *NCSP* are non-commercial long, short, and spread positions, respectively. De Roon et al. (2000)[12] calculated the *PNL* for reported commercials and referred to it as "hedging pressure", and Sanders et al. (2004)[6] used *PNL* of non-commercial positions in energy futures markets to determine if any relationships existed between trader positions and market prices. Here, we follow the literature and make use of *PNL* of non-commercial positions and *PNL* of managed money as the indicator to describe speculative trading activities.

Because the historical data of DCOT report are back to June 13, 2006, therefore study sample of this paper is from June 13, 2006 to Dec. 28, 2010. We study the relationship between the traders' position and the price or returns of crude oil futures, with weekly data. The COT and DCOT data reflect traders' positions as of Tuesday's close; thus, a matching set of futures returns calculated by Tuesday-to-Tuesday closing prices is used. Fig. 1 gives a description of crude oil price and traders' positions. First, we study the correlation of price and positions, with the results reported in Table 2. We can see that non-commercial position and managed money position have a positive correlation with price or return. And non-commercial net long position has a very strong positive correlation with managed money net long position, with a correlation coefficient 0.85. This indicates that non-commercial position is a good proxy for managed fund position.

Table 1. The descriptive statistics of price and return, and the autocorrelation partial correlation of return and squared return

				return				squared return			
Statistics	price	Return	lags	AC	PAC	Q-Stat	Prob	AC	PAC	Q-Stat	Prob
Mean	76.58164	0.001217	1	0	0	2.00E-05	0.997	0.416	0.416	41.465	0.0000
Median	73.75	0.00364	2	0.017	0.017	0.0665	0.967	0.201	0.034	51.156	0.0000
Maximum	140.97	0.218881	3	0.103	0.103	2.6238	0.453	0.19	0.116	59.934	0.0000
Minimum	34.93	-0.25143	4	0.059	0.059	3.4694	0.483	0.201	0.098	69.789	0.0000
Std. Dev.	21.0667	0.0559	5	0.022	0.02	3.5921	0.61	0.224	0.115	82.089	0.0000
Skewness	0.8293	-0.3407	6	0.05	0.038	4.197	0.65	0.238	0.106	95.98	0.0000
Kurtosis	3.8603	5.1763	7	0.08	0.069	5.7886	0.565	0.201	0.046	105.89	0.0000
Jarque-Bera	34.6197	51.3546	8	0.079	0.073	7.3135	0.503	0.276	0.17	124.7	0.0000
Probability	0	0	9	0.161	0.154	13.727	0.132	0.336	0.166	152.75	0.0000
Observations	238	237	10	0.011	-0.004	13.756	0.184	0.206	-0.035	163.35	0.0000

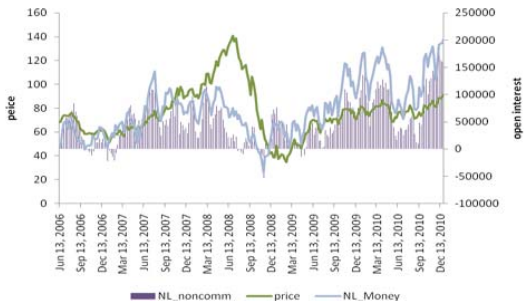

Fig. 1. Crude oil futures price and the positions of two kinds of traders

Table 2. The correlation of price and positions

	price	return	NL_noncomm	PNL_noncomm	NL_Money
NL_noncomm	0.213347	0.168908			
PNL_noncomm	0.152784	0.174699	0.977962		
NL_Money	0.362331	0.209796	0.850269	0.784638	
PNL_Money	0.228046	0.205818	0.818919	0.782026	0.964155

Based on the augmented Dickey-Fuller (ADF) unit root test, crude oil price series, net long of managed money (recorded as *MNL*), and percent net long of managed money (recorded as *MPNL*) are not stationary even at 10% significant level, while net long of non-commercial (recorded as *NNL*) and percent net long of non-commercial (*NPNL*) are stationary at 5% significant level, but not significant at 1% level. The Johansen cointegration test of price and *MNL* based on no intercept or trend in equations or test and 2 lag intervals assumptions indicates that 1 cointegrating equation at the 5% level.

3. Granger causality test

Next, we study the relationship between speculative positions and returns of crude oil futures using Granger causality test (Granger, 1969, 1980) [13,14] with weekly data. The crude oil futures weekly returns and percent net long of non-commercial and managed money (*NPNL, MPNL*) series are all stationary series based on the augmented Dickey-Fuller (ADF) unit root test. We use stationary series, i.e. returns and percent net long, to set up the model and make the test. We firstly set up the model shown as equation (2) and (3) and then process instantaneous Granger causality test shown as equation (4) and (5). The lag structure (m,n) for each OLS regression is determined to minimize Akaike information criterion (AIC). To make sure the equation is specified correctly, we use Lagrange Mutiplier (LM) test to examine the serial correlation of the residuals. If there exists serial correlation, we will add lags of independent variables. We also test the homoscedasticity of residuals, and we use White's heteroscedastic consistent covariance estimator of coefficient if there exits heteroscedasticity. We use both the percent net long of non-commercial positions and that of managed money to make the test.

For equation (2), the null hypothesis is $H_0:\theta_j=0$ for each j. If this null hypothesis is rejected, that means returns lead positions. For equation (4), the null hypothesis is $H_0:\theta_0=0$ and $\theta_j=0$ for each j. For equation (3), the null hypothesis is $H_0:\beta_j=0$ for each j. For equation (5), the null hypothesis is $H_0:\beta_0=0$ and $\beta_j=0$ for each j. If this null hypothesis is rejected, that means positions lead returns. We use Wald coefficient test to test the hypothesis. The results of Granger causality test are reported in Table 3.

$$PNL_t=\varphi+\sum_{i=1}^{m}\lambda_i PNL_{t-i}+\sum_{j=1}^{n}\theta_j R_{t-j}+\varepsilon_t \tag{2}$$

$$R_t=\alpha+\sum_{i=1}^{m}\gamma_i R_{t-i}+\sum_{j=1}^{n}\beta_j PNL_{t-j}+\varepsilon_t \tag{3}$$

$$PNL_t=\varphi+\sum_{i=1}^{m}\lambda_i PNL_{t-i}+\theta_0 R_t+\sum_{j=1}^{n}\theta_j R_{t-j}+\varepsilon_t \tag{4}$$

$$R_t=\alpha+\sum_{i=1}^{m}\gamma_i R_{t-i}+\beta_0 PNL_t+\sum_{j=1}^{n}\beta_j PNL_{t-j}+\varepsilon_t \tag{5}$$

Table 3. Granger causality test between returns and percent net long positions

	Granger causality test		instantaneous Granger causality test	
Null hypothesis	Returns don't lead *NPNL*	*NPNL* don't lead returns	Returns don't lead *NPNL*	*NPNL* don't lead returns
(m,n)[a]	1,3	1,1	1,2	1,1
F-statistic[b]	2.7622(0.0429)	0.0039(0.9505)	14.9715 (0.0000)	22.1353(0.0000)
χ^2-statistic	8.2866(0.0404)	0.0039(0.9505)	47.9145 (0.0000)	44.2707(0000)
Impact[c]	(+)*		(+)*	(+)*
Null hypothesis	Returns don't lead *NPNL*	*NPNL* don't lead returns	Returns don't lead *NPNL*	*NPNL* don't lead returns
(m,n)	1,1	1,1	1,1	1,1
F-statistic	2.8191(0.0945)	0.0455(0.5099)	23.177(0.0000)	31.6593(0.0000)
χ^2-statistic	2.8191(0.0931)	0.0455(0.5099)	46.3545(0.0000)	63.3186(0.0000)
Impact	(+)*		(+)*	(+)*

a. The lag structure (m,n) for each OLS regression.

b. The p-value from the Wald F-test and Chi-squared test of the null is in the parentheses.

c. The cumulative impact of lagged values of the tested variable. For example, for Eq. (a-1) of note (a), (+) or (-) is the sign of $\sum\theta_j$, and an asterisk (*) denotes a rejection of the null at the 10% level (Wald Chi-squared test).

From the empirical results, we find that there exists a unidirectional Granger causality from returns to percent net long positions held by speculative traders, while a bi-directional instantaneous Granger causality exists between returns of crude oil and percent net long positions. These results are similar to the findings of Sanders et al. (2004)[6], i.e. non-commercial positions do not contain any predictive information about returns, while positive futures returns result in non-commercial net long positions increasing in the following week.

When we analyze these results carefully, we can find out that the difference between Granger causality test and instantaneous Granger causality test tells us that the position changes cause the crude oil price movement. Thus, taking the managed money position as an example, we can express our results as follows:

$$MPNL_t=0.0099+0.9302MPNL_{t-1}+0.06493R_{t-1} \tag{6}$$

[0.0035] [0.0266] [0.0386] adjusted R^2=0.8657

$$R_t = 9.55\times10^{-5} - 0.036R_{t-1} + 0.8217D(MPNL_t) \qquad (7)$$

[0.0033] [0.0589] [0.1082] adjusted R^2=0.1915

where $D(X_t) = X_t - X_{t-1}$, and the number in square brackets below the estimated coefficient is the standard error. From the results we can clearly see that returns lead the positions, while the changes of position held by speculative funds will cause the price movement. The effect of position changes on crude oil price movement is strong, with a coefficient 0.8217. Because returns lead non-commercial and managed money positions, this could be indicative of a class of positive feedback traders, described as trend followers by De Long et al. (1990)[15]. Because speculative traders' net long positions influence crude oil returns, when we modelling the price dynamics of crude oil futures price in short run, we should identify changes of speculative positions as a determinant factor, i.e. an explanatory variable.

4. GARCH model of crude oil futures returns and its implications

The test results of statistics of crude oil futures returns mentioned in Table 1 have shown the existence of conditional heteroscedasticity of return series. Though the autocorrelation (AC) of returns suggests the series has no significant serial correlations, the AC of squared returns clearly suggests that the returns are not independent. Combining these patterns, it seems that the returns are indeed serially uncorrelated, but dependent. The Ljung-Box statistics (Q-Statistics) for autocorrelation also show the existence of conditional heteroscedasticity. Therefore, GARCH model can fit the return series. Sadorsky(2006)[16] has shown that the GARCH model fits well for crude oil price and volatility, and GARCH model is a popular way to modeling the volatility of crude oil. Thus, we take use of GARCH model as the tool to do analysis. Bollerslev(1986)[17] proposed the generalized autoregressive conditional heteroscedastic (GARCH) model to capture the properties of volatility clusters of time series. The GARCH (1,1) model has been widely used in modeling uncertainty in financial assets returns. It provides a measure of conditional volatility in the presence of time-varying second-order moments, expressed as:

$$R_t = \mu + \varepsilon_t \text{, where } \varepsilon_t \left| \Omega_{t-1} \sim N\left(0, \sigma_t^2\right)\right., \qquad (8)$$
$$\sigma_t^2 = \omega + \alpha_1\varepsilon_{t-1}^2 + \beta_1\sigma_{t-1}^2$$

where R_t is the return at time t, μ is a constant, ε_t is serially uncorrelated errors (innovations) of returns with mean zero, while σ_t^2 is the conditional variance of ε_t. Coefficients α_1 and β_1 reflect the dependence of the current volatility on its past levels, and the sum $\alpha_1 + \beta_1$ indicates the degree of volatility persistence.

In this paper, we want to investigate some interesting issues besides capturing the volatility clusters of time series of crude oil futures returns. From the results above, non-commercial traders or managed money traders are positive feedback traders or trend followers. When the return of crude oil futures is good, positive feedback traders will increase the positions of crude oil futures. And because position changes of speculative traders can affect contemporary return, we can infer that return should be auto-correlated with at least 1 lag. However, from the autocorrelation of return series in Table 1, we know that return series has no significant serial correlations. Then we can infer that maybe the information of price movement is conveyed by other variables rather than directly by itself, for example speculation positions. Based on this analysis and the results from above section, we know that changes of speculative positions may be a determinant factor of price movement. Thus, we bring this factor into the GARCH model to modelling the effects of speculation. Based on asset pricing model in financial economic theory, if there exists the rational traders in the market, return should be determined by the risk. We can use variance as the risk measure, and bring the conditional variance in to the GARCH model, i.e. set up a GARCH-M model, to test whether the relationship between return and risk exists. This result can also tell whether there exist the rational traders in crude oil futures market. To accomplish the above analysis, we use the GARCH model that allows exogenous variables to affect the conditional mean. The exogenous variables are non-commercial or managed money percent net long position changes, and conditional variance. For different issue that we try to test, we will choose different exogenous variables into the model. By comparing the empirical results of each model that contains different exogenous variables, we can determine how the factors influence crude oil futures prices and volatility.

From the Jarque-Bera statistic of returns series in Table 1, the probability value shows we can reject the null hypothesis of a normal distribution. Therefore, in this paper we will use a GARCH model with student-t distribution innovation to capture of flat-tail property of innovations. All of the GARCH models are estimated using the method of maximum likelihood. The number of ARCH term and GARCH term orders in the model is chosen to minimize the Akaike information criterion. After the estimation of GARCH model, we also need to test of residuals, coefficients, and goodness of fit of the model. We provide the estimation results of GARCH models in Table 4.

Table 4. The estimation results of GARCH models with Student-t innovation

Mean Equation	(1)	(2)	(3)	(4)	(5)
μ	0.003761 (0.73)	0.004252(1.65)*	0.00249(0.65)	0.002905 (1.33)	0.003119 (1.02)

σ_t^2	0.227957 (0.13)		0.93842(0.54)		-0.239187 (-0.15)
D(NPNL)		1.225235(8.35)***	1.228382(8.35)***		
D(MPNL)				0.762064(10.81)***	0.784438(10.8)***
Variance Equation					
ω	0.0002 (1.58)	0.000124 (1.59)	0.000158(1.39)	0.000101 (1.71)*	0.000146 (1.58)
ε_{t-1}^2	0.17586 (2.62)***	0.148795 (2.12)**	0.179117(2.19)**	0.216592 (2.41)**	0.2654 (2.36)**
σ_{t-1}^2	0.75008 (8.52)***	0.795492 (8.75)***	0.749077(6.37)***	0.743457 (8.75)***	0.677876 (6.16)***
T-DIST. DOF	7084642	12.29564	12.70911	10.43312	9.155431
Log likelihood	378.6711	411.2363	409.1744	429.8519	427.0491
Adjusted R-squared		0.131366	0.11298	0.176052	0.178214
F-statistic		8.138176***	6.00991***	11.08515***	9.529877***
ARCH test: F-statistic	1.31 [0.2533]	0.3021[0.5831]	0.1553[0.6939]	0.0465[0.8293]	0.0109[0.9164]
volatility persistence	0.92594	0.945387	0.928194	0.9600	0.943276
Unconditional variance	0.0027	0.0022	0.0022	0.0027	0.0025

[a] The results are reported in equations of mean and variance. Each column contains the coefficient of the variable, the z-statistics are in parentheses, and the asterisk (*) denotes significance. *** (**, *) denote significance at 1% (5%, 10%) level.

[b] We also provide ARCH LM diagnostic tests of residuals of the model. Results of ARCH LM test are obtained with 1 lag. The p-values of the diagnostic statistics are presented in square brackets.

From Table 4, we can see that the estimates meet the general requirement of a GARCH(1,1) model. The general GARCH(1,1) model with student-t distribution innovation or the GARCH(1,1)-M model without exogenous variable cannot fit the weekly return of crude oil futures very well. If we bring the position changes of speculative traders into the mean equation shown in column (2)-(5) of Table 4, we find out that this factor has some explanatory power for weekly return, and is significant in the mean equation, no matter what proxy we use, non-commercial or managed money positions. To investigate whether returns are related to risks, we introduce conditional variance into the mean equation, as the model shown in column (1), (3) and (5). All of the results show that conditional variance is not significant in the model, which means return is not determined by risk. The estimates of all models meet the general requirement of a GARCH (1, 1) model, the F-statistics of ARCH LM test of these models indicating no ARCH effect any more. When we compare these models, model in column (4) is best fitted the data, with maximum Log likelihood. From this results, we find out managed money positions is better than non-commercial positions as a proxy of speculation to explain the return series. We use model in column (4) as an example, we can express our study model as follows:

$$R_t = \mu + D\left(MPNL_t\right) + \varepsilon_t ,$$
$$\text{Where } \varepsilon_t \left|\Omega_{t-1}\right. \sim \text{Student-t (n)}, \tag{9}$$
$$\sigma_t^2 = \omega + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2$$

The sum $\hat{\alpha}_1 + \hat{\beta}_1$ indicates the degree of volatility persistence, which is around 0.93 to 0.96 for all these models. This indicates the strong volatility clusters in crude oil futures weekly returns.

From the model results in column (4) of Table 4, we see that coefficient of $D\left(MPNL_t\right)$ is 0.76, the coefficients of ARCH (1) term and GARCH (1) term are 0.22 and 0.74, respectively. This indicates that if the percent net long of managed money increased by 1%, the return will increase 0.76%. The speculation effect in not small. And for the conditional variance, large ε_{t-1} and σ_{t-1}^2 give rise to a large σ_t^2. This means that a large ε_{t-1}^2 tends to be followed by another large ε_t^2, generating, again, the well-known phenomenon of volatility clustering. For a GARCH (1, 1) model, the multistep ahead volatility forecasts converge to the unconditional variance of ε_t, as the forecast horizon increases to infinity, provided that $Var(\varepsilon_t)$ exists. The unconditional variance of ε_t in the GARCH (1, 1) model can be calculated by $\omega/(1-\beta_1-\gamma_1)$. The unconditional variance calculated by the GARCH (1, 1) model shown as equation (9) is 0.0027. Furthermore, we calculate the variance series estimated by this GARCH model and depict the variance series in Fig. 2. We can see that there is an extreme large conditional variance during Sep. 2008 to Apr. 2009, with the maximum variance 0.0246 reached at Jan. 20, 2009. When we combine the results shown in Fig. 2 and Fig. 1, we find out that during the period of very large conditional variance, the percent net long of managed money (MPNL) fluctuate largely, even from the net long position to net short position. This make crude oil futures price drop quickly, which follows by a large volatility clustering.

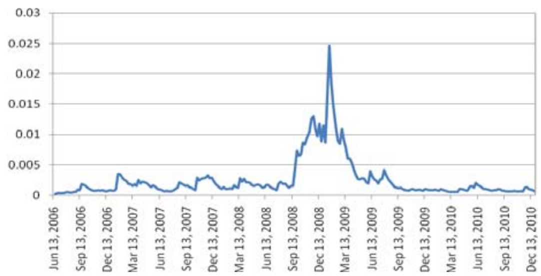

Fig. 2. Conditional variance series estimated by the GARCH model

5. Conclusion

Price dynamic and volatility has some inherent characteristics that are commonly seen in assets returns. Understanding the behaviour of volatility is important, because it is useful in derivatives valuation, hedging decisions, and decisions to invest in physical capital tied to production or consumption. Furthermore, volatility is important in risk management. Volatility modelling provides a simple approach to calculating value at risk of a financial position. Finally, modelling volatility of a time series can improve the efficiency of parameter estimation and the accuracy of interval forecasts (Tsay, 2002) [18]. Thus, this study can illustrate the price discovery process in crude oil futures market, and is helpful for risk management and financial engineering.

This paper discusses whether there are some other new factors that influence price volatility, in addition to market fundamentals, as stated by theories of storable commodities' prices, when the importance of commodities as common investment alternatives to traditional markets has increased. Using WTI crude oil futures prices as the study object, this paper concentrates on investigating whether trading activities of speculative traders have a significant effect on crude oil price and its volatility. We also reveal the characters of trading activities of speculative traders, and study how this factor influences crude oil futures returns and volatility. From the empirical results, we find that there exists a unidirectional Granger causality from returns to percent net long positions held by speculative traders, which indicates non-commercial traders or managed money are a class of positive feedback traders or trend followers. Because a bi-directional instantaneous Granger causality exists between returns of crude oil and percent net long positions, the changes of position held by speculative funds will cause the price movement. Therefore, when we modelling the price dynamics of crude oil futures price in short run, we can identify changes of speculative positions as a determinant factor into the model.

Based on the statistics of return series, we set up the GARCH (1, 1) model that allows exogenous variables to affect the conditional mean with Student-t distribution innovation. From the estimation results, we verify position changes of non-commercial or managed money traders can impact crude oil futures returns significantly. When speculative traders increase the percent net long position, the price will rise; otherwise, crude oil will fall. We also find that the conditional variance is not a determinant of crude oil futures weekly return. This indicates that rational traders who make investment decision by compare the return and risk is not enough in crude oil futures market, most of the traders are speculative traders, who are positive feedback traders or trend followers. Because speculative traders are trend followers, if the return of crude oil futures is good, the speculator is willing to increase their net long positions, and this trading activity can push up the crude oil futures price higher. Then, we can see the crude oil futures price become higher and higher. Speculation contributes very much to this price movement.

During the period the financial crisis, there is an extreme large conditional variance. Observing the data carefully, we find out that during this period, the percent net long of managed money (*MPNL*) fluctuate largely, even from the net long position to net short position. This make crude oil futures price drop quickly, which follows by a large volatility clustering.

These results have profound implications for crude oil futures market supervision and risk management. First, regulatory authority and investors, especially hedgers, should pay close attention to trading activities of speculative traders. They are indeed an important determinant of crude oil futures price level. By changing positions, non-commercial traders or managed money traders can push up and down crude oil futures price. Second, if regulatory authority can provide more detailed data about different kinds of traders to the public, analysts and researchers can better understand the relationship between speculative activities and crude oil price, and thereby can give more accurate forecast of crude oil price.

6. Copyright

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